Communications of the Association for Information Systems

Volume 52 Paper 34

6-19-2023

Extraordinary Claims Require Extraordinary Evidence: A Comment on "Recent Developments in PLS"

Pratyush N. Sharma
The University of Alabama, pnsharma@cba.ua.edu

Benjamin D. Liengaard
Aarhus University

Marko Sarstedt
Ludwig-Maximilians-University Munich, Germany Babeș-Bolyai University

Joseph F. Hair
University of South Alabama

Christian M. Ringle
Hamburg University of Technology

Follow this and additional works at: https://aisel.aisnet.org/cais

Recommended Citation

Sharma, P. N., Liengaard, B. D., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2023). Extraordinary Claims Require Extraordinary Evidence: A Comment on "Recent Developments in PLS". Communications of the Association for Information Systems, 52, 739-742. https://doi.org/10.17705/1CAIS.05234

This material is brought to you by the AIS Journals at AIS Electronic Library (AISeL). It has been accepted for inclusion in Communications of the Association for Information Systems by an authorized administrator of AIS Electronic Library (AISeL). For more information, please contact elibrary@aisnet.org.

Communications of the Association for Information Systems

Debate Article DOI: 10.17705/1CAIS.05234 ISSN: 1529-3181

Extraordinary Claims Require Extraordinary Evidence: A Comment on "Recent Developments in PLS"

Pratyush N. Sharma

The University of Alabama, USA

pnsharma@cba.ua.edu

Benjamin D. Liengaard

Aarhus University, Denmark

Marko Sarstedt

Ludwig-Maximilians-University Munich, Germany

Babeș-Bolyai University, Romania

Joseph F. Hair

University of South Alabama, USA

Christian M. Ringle

Hamburg University of Technology, Germany

Abstract:

Evermann and Rönkkö (2023) review recent developments in partial least squares (PLS) with the aim of providing guidance to researchers. Indeed, the explosion of methodological advances in PLS in the last decade necessitates such overview articles. In so far as the goal is to provide an objective assessment of the technique, such articles are most welcome. Unfortunately, the authors' extraordinary and questionable claims paint a misleading picture of PLS. Our goal in this short commentary is to address selected claims made by Evermann and Rönkkö (2023) using simulations and the latest research. Our objective is to bring a positive perspective to this debate and highlight the recent developments in PLS that make it an increasingly valuable technique in IS and management research in general.

Keywords: Partial Least Squares, PLS, Structural Equation Modeling, SEM.

This manuscript underwent editorial review. It was received in 2021. John Venable served as Associate Editor.

1 Introduction

Extraordinary claims require extraordinary evidence (Sagan, 1989). In their recent *CAIS* article, Evermann and Rönkkö (2023) make extraordinary claims regarding the alleged damage caused by the adoption and use of partial least squares (PLS) in information systems (IS) research. They not only cast doubt on the latest methodological research on PLS, but also on twenty-five years' worth of foundational IS research using PLS, including the validity of the seminal articles by many distinguished scholars in the field (Table 1 in Evermann and Rönkkö, 2023). Given the seriousness of these claims, one would expect thorough and irrefutable evidence, but Evermann and Rönkkö (2023) fail to provide such evidence. This disregards decades of hard-earned achievements by IS researchers. Our goal in this short commentary is to address selected claims made by Evermann and Rönkkö (2023) and allay the concerns regarding the use of PLS by providing a constructive assessment of its abilities. We hope to bring a positive perspective by highlighting that PLS is a valuable technique in IS research.

2 Questionable Claims

Evermann and Rönkkö (2023) make several questionable claims, some more subtle than others. As addressing all of them is beyond the scope of a short commentary, we focus on the following: (1) PLS as a known-to-be biased estimator, (2) PLS finds itself between a "rock and hard place" (i.e., explanation and prediction), (3) research is retrofitting PLS with "kludges upon kludges," (4) PLS is unreliable in measurement error correction and inference testing, and (5) the premature adoption of PLS casts doubts on the validity of seminal studies and has caused significant damage to the field.

2.1 Claim 1: PLS is a Known-to-be Biased Estimator.

In section 2.3 ("Known Limitations") of their paper, Evermann and Rönkkö (2023) discuss the "PLS bias," which refers to the fact that PLS underestimates structural model relationships and overestimates measurement model relationships when the data originate from a common factor model. However, Evermann and Rönkkö's (2023) discussion provides an incomplete explanation of the deliberate design choices made by the pioneers of structural equation modeling (SEM), thereby creating unnecessary doubt among researchers applying the method. Worse, Evermann and Rönkkö's (2023) discussion can lead behavioral researchers to mistakenly equate PLS bias with "error" or "wrongness." Evermann and Rönkkö (2023) cite both Wold—the originator of PLS—and Jöreskog—the originator of covariance-based structural equation modeling (CBSEM)—to state that bias in PLS has been well-known since its inception. Evermann and Rönkkö (2023), however, seem surprised by the subsequent adoption of PLS and note the following "one has to wonder why the IS discipline thought that adopting a designed-to-be-biased estimator for the common factor model was a good idea. This is of course a rhetorical question." Unfortunately, this rhetorical question suggests that Evermann and Rönkkö (2023) are either unaware of, or disagree with, the common knowledge in statistical literature that bias is just one aspect on which to evaluate the suitability of a method (e.g., Friedman, 1997; Geman et al., 1992; Hastie et al., 2009). Evermann and Rönkkö's (2023) statement seems even more surprising given that the justification behind PLS bias often appears a few sentences away from the portions they selectively quote to make their case (see Jöreskog & Wold, 1982, p. 266; Wold, 1982, p. 28). In doing so, Evermann and Rönkkö (2023) ignore Jöreskog and Wold's nuanced views of CBSEM and PLS and why they considered the methods "complementary rather than competitive" (Jöreskog & Wold, 1982, p. 270).

What was the purpose of introducing bias into PLS, and more importantly, why would Wold and Jöreskog propagate a known-to-be-biased method? This was explicitly addressed by Jöreskog and Wold (1982, p. 266) who note that "the primary purpose of the ML approach is to study the structure of the observables as reflected by their dispersion (variance-covariance) matrix…the primary purpose of the PLS approach is to predict the indicators…" To achieve the goal of prediction, Wold (1982, p. 52) specifically mentions that "there is here a trade-off between estimation bias and reduction of standard errors." It is well-known that bias is just one element of the bias-variance tradeoff that is necessary to achieve the goal of prediction, and that optimal prediction does not require unbiased coefficient estimates (Shmueli & Koppius, 2011). In fact, ensuring zero bias in coefficient estimates creates major problems for out-of-sample predictions, and techniques that focus solely on unbiasedness provide inferior predictions (Kleinberg et al., 2015). In this vein, Hastie et al. (2009, p. 52) remark that "from a more pragmatic point of view, most models are distortions of the truth, and hence are biased; picking the right model amounts to creating the right balance between bias and variance." It may come as a surprise to some readers to learn that multilevel techniques deliberately bias cluster estimates (through "shrinking" or "pooling") toward estimated population averages (Yarkoni & Westfall, 2017). Techniques such as Lasso regression also produce intentionally biased estimates to improve prediction (Ranstam & Cook, 2018).

The interplay between bias and variance is also reflected in the two SEM approaches: (1) the "hard" causal-explanation approach where one is interested in the optimal estimation of coefficients (unbiased $\hat{\beta}$) *in a given sample* (CBSEM and consistent PLS) (Dijkstra, 2014; Dijkstra & Henseler, 2015),[1] and (2) the "soft" causal-predictive approach followed by PLS where the goal is to balance the prediction of unseen cases (low error in $\hat{Y}$) while providing consistent-at-large, but not necessarily unbiased, $\hat{\beta}$ estimates with the aim of *generalizing* out-of-sample (Wold, 1982).[2] The latter approach requires a trade-off, where PLS sacrifices in-sample optimality for the ability to conduct out-of-sample prediction by producing explicit latent variable case values (Shmueli et al., 2016). Not surprisingly, PLS outperforms CBSEM and other methods in prediction (Becker et al., 2013; Evermann & Tate, 2016), while at the same time producing a small bias which is of no practical concern in the vast majority of explanatory studies—as extensively documented in early writings on PLS (e.g., Apel & Wold, 1982) and in numerous simulation studies contrasting CBSEM and PLS (e.g., Reinartz et al., 2009; Sarstedt et al., 2016). That PLS bias is generally small is also evidenced in our simulation results (Section 2.5 below), which show marginal differences between PLS and CBSEM estimates under the specific conditions that Evermann and Rönkkö (2023) claim as problematic; that is, under common factor model population with zero or weak effects. Perhaps a simple analogy is in order: a car engine that is designed to balance horsepower with mileage is expected to be different than engines that solely optimize either horsepower or mileage. The crucial takeaway is that all statistical techniques make certain functional tradeoffs that researchers need to be aware of.

With regard to assessing the out-of-sample predictive abilities in PLS, as pointed out in recent research (Sarstedt & Danks, 2022; Sharma et al., 2019), the R^2 metric is unsuitable for this specific purpose—yet it remains a useful measure of explained variance and potential overfit. Instead, through the cross-validation procedure, PLS uses the data itself to effectively simulate the bias-variance tradeoff and out-of-sample inferential tests and metrics (Liengaard et al., 2021; Shmueli et al., 2016). This opens avenues for the assessment of out-of-sample abilities of IS models. Thus, PLS models can serve as a bridge between fully explanatory and fully predictive models (Hair & Sarstedt, 2021).

2.2 Claim 2: PLS Finds Itself between a Rock and Hard Place

We are astounded by Evermann and Rönkkö's (2023) claim that "users of predictive models may be unwilling to accept lower predictive performance when all that is gained is a theoretically plausible, linear model. This trade-off between prediction and explanation is specific to every application, but is unlikely to always go well for PLS (or any other linear structural equation modeling method)." As a result, Evermann and Rönkkö (2023) claim that PLS finds itself between a "rock and hard place" (i.e., between explanation and predictive techniques).

This is incorrect. Explanation and prediction are not an "either-or," zero-sum game that Evermann and Rönkkö (2023) make it out to be. Evermann and Rönkkö (2023) assume that researchers will either be in the "explanation" or "prediction" mode, but not simultaneously both. Their stance goes against Gregor's (2006) typology that identifies "explanatory-predictive" theories as one important class of IS theories. While approaches like neural networks or random forests provide high levels of predictive power, they are virtual interpretation black boxes. Prediction devoid of explanation is uninterpretable, while explanation devoid of predictive ability is questionable.

If prediction without regard to the "gain" of a theoretical model was the only scientific goal, then we should not expect to see world-renowned machine-learning researchers making urgent calls to improve the interpretability of their computational models (Athey, 2017; Chernozhukov et al., 2018; Hofman et al., 2017; Hofman et al., 2021; Wager & Athey, 2018). On the flip side, there have been numerous calls to improve the predictive abilities of behavioral models (Hofman et al., 2017; Shmueli & Koppius, 2011; Yarkoni & Westfall, 2017). Clearly, there is great interest in merging prediction with explanation in both behavioral and computational social science communities. In fact, in their recent *Nature* article Hofman et

[1] However, as the models become more complex CBSEM's optimality aspirations also become untenable and "more or less illusory" (Wold, 1982, p. 53).

[2] On the other extreme, purely predictive machine-learning techniques are fine-tuned to provide best out-of-sample prediction (i.e., lowest error in $\hat{Y}$) but provide no guarantees regarding $\hat{\beta}$ (Kleinberg et al., 2015).

al. (2021) recommend an “integrative modeling” approach that simultaneously considers explanation and prediction. Explanation and prediction, while philosophically compatible, require an empirical tradeoff in practice, as we discussed above (Shmueli & Koppius, 2011). Prediction is not a free lunch. Thus, to claim that researchers interested in combining explanation with prediction to create strong theory will be unwilling to make the tradeoff is presumptuous and without foundation. Contrary to Evermann and Rönkkö's (2023) assertion, a theoretically plausible model that provides a solid explanation of the underlying processes with adequate predictive ability is an extremely useful device (Shmueli, 2010). Such models help lay the foundation for future models with more accurate explanatory and predictive abilities. Indeed, PLS was deliberately designed to occupy the demanding space “between a rock and hard place,” that is, explanation and prediction (Wold, 2006).

2.3 Claim 3: Research is Retrofitting PLS with Kludges upon Kludges

On the one hand, Evermann and Rönkkö (2023) exhort researchers to not only “debate and argue back and forth about the merits of PLS, but to make significant progress in improving it and its use in applied research.” On the other hand, they complain that research is trying hard to “retrofit” PLS with additions that come naturally to the mathematically elegant CBSEM, and as a result PLS appears kludgy. Indeed, the quest for mathematical elegance is a personal driving force for many scientists. However, as Nobel laureate Steven Weinberg has said in this vein, “The universe doesn’t care about what makes theoretical physicists happy” (Greene, 2015). For all their limitations and retrofitted kludges, the “standard model of particle physics” and the “periodic table of elements” remain among the most successful predictive models of all time.

In contrast to what Evermann and Rönkkö (2023) assert, retrofitting (i.e., adding a component or ability not available in the initial design) is a valid, valuable, and inescapable fact in engineering and sciences. Consider these additional examples: String theory retrofitting quantum theory onto strings, retrofitting of radiocarbon dating protocols, retrofitting software using patches and updates, and the retrofitted protocols on which the entire Internet runs. Indeed, good designs leave room for future improvements and additions, and ones that do not run the risk of becoming evolutionary dead-ends. In this sense, PLS’s flexibility is an advantage. All scientific methods rely on continual fine-tuning and creation of scaffoldings to make sure they perform well as knowledge regarding their limitations and strengths accumulates. Thus, the goal of IS researchers should be to use this power responsibly (Petter & Hadavi, 2021).

Importantly, not all additions to PLS come naturally to CBSEM (e.g., out-of-sample predictions). Evermann and Rönkkö (2023) further ask: what can be gained from such additions when researchers have CBSEM at their disposal? The answer is simple: because the central goal of PLS differs from CBSEM, the additions to PLS should not be seen as directly competing with CBSEM, as Evermann and Rönkkö (2023) do, but rather as complementary (see also Jöreskog & Wold, 1982), and help improve its ability to assess explanatory-predictive models. Complex socio-technical processes that give rise to noisy multivariate data do not care about what makes statisticians happy, or whether they believe in common factors or composites. Data simply are. The onus is on researchers to arm themselves with multiple tools of assessment and utilize them responsibly (Petter, 2018).

2.4 Claim 4: PLS is Unreliable in Measurement Error Correction and Inference Testing

Evermann and Rönkkö (2023) claim that PLS results are less reliable than sum scores and do not allow for inference testing. As evidence they cite their previous study (Rönkkö & Evermann, 2013), which has been criticized by scholars for its extremely sparse simulation design that does not allow for drawing generalizable conclusions (Henseler et al., 2014; Rigdon, 2016). Specifically, their study relied on an unrealistically simplified two-construct model with a zero relationship, a known boundary condition of PLS (Lohmöller, 1989; Wold, 2006)[3]. Evermann and Rönkkö (2023) acknowledge that this condition “breaks the method” and that these problems do not occur in other conditions, yet they claim that this is “precisely that condition when it [i.e., PLS] is used by applied researchers.” For this to have merit, two conditions must be *simultaneously* met. First, a vast majority of PLS path models must include two constructs that are *not* embedded in a larger nomological network of constructs (i.e., there are no significant effects going

[3] While testing methods for their extreme boundary conditions is useful in some situations, it doesn’t necessarily justify conclusions under normal, real-world conditions. For instance, showing that a car has problems running at -30° Celsius does not mean the car does not perform in normal temperatures.

into any of the two constructs). Second, the effect between the two constructs under consideration must be zero in the population.

As for the first condition, Evermann and Rönkkö (2023) note: “Indeed, a review by Goodhue et al. (2015) concluded that such models are common in IS research and thus a large share of PLS-based IS research may be susceptible to this issue.” However, Goodhue et al. (2015, p. 11) did not conduct a “review” of published studies, but only note in passing that “a *scan* of models tested in MISQ revealed many [i.e., models] that included at least one construct with a single path into or out of it” (emphasis added). This hardly qualifies as evidence showing that “a large share of PLS-based IS research may be susceptible to this issue” as Evermann and Rönkkö (2023) claim.

Regarding the second condition, Evermann and Rönkkö (2023) implicitly assume zero-effects are commonplace. This is in sharp contrast to Hofman et al. (2021, p. 182) who note that “in the complex world of human and social behaviour it is highly likely that many effects are non-zero.” This is also corroborated by a recent meta-analysis of published unified theory of acceptance and use of technology (UTAUT) studies by Blut et al. (2022) who assessed 25,619 effect sizes reported by 737,112 users in 1,935 independent samples. While their meta-analysis finds significant variation in effect sizes (due to possible moderators), they find hardly any zero-effects and only very few relatively small effects (Blut et al., 2022).

Considering the above, it is not surprising that none of the seminal models (Table 1 in Evermann and Rönkkö, 2023) assessed a PLS path model that meets these conditions. In fact, on reviewing the seminal models, we identified only 6 out of 124 (4.84%) path relations where a dependent construct is explained by only one independent construct in an isolated part of the model.[4] Moreover, coefficients in these six path relations vary between 0.23 and 0.81 with an average of 0.448, and all are significant at the 5% level. These findings put Evermann and Rönkkö's (2023) assertion on extremely thin ice.

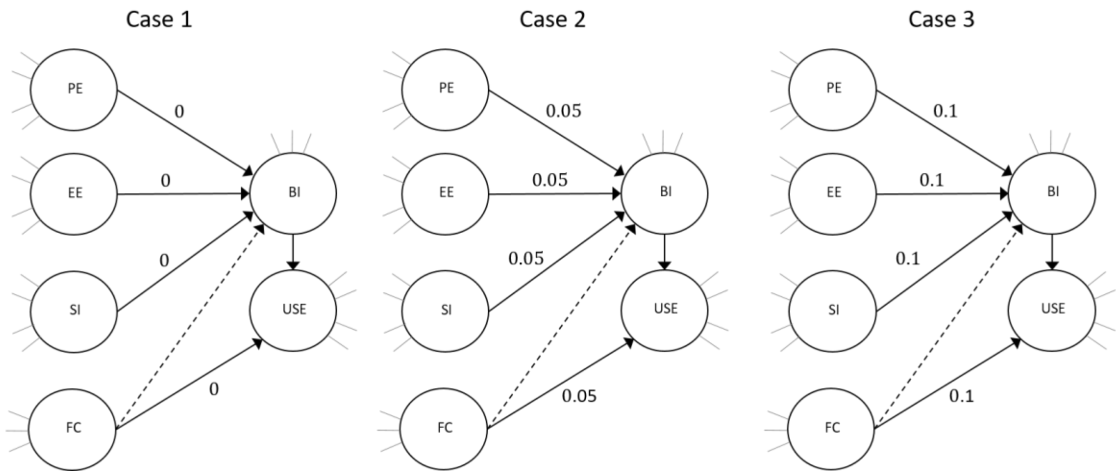
2.5 Claim 5: Premature Adoption of PLS Casts Doubts on the Validity of Seminal Studies and Caused Significant Damage to the Field

Perhaps the most extraordinary claim Evermann and Rönkkö (2023) make is “the adoption of PLS in the IS discipline was premature and this now casts *significant* doubts on the validity of seminal studies” [emphasis added]. In effect, Evermann and Rönkkö (2023) cast doubt on foundational IS research by renowned scholars that have been replicated hundreds, in most cases thousands of times (Table 1 in Evermann and Rönkkö, 2023) without providing real evidence. Evermann and Rönkkö's (2023) counterfactual rhetorical device implies that, *ceteris paribus*, if researchers had used CBSEM or consistent PLS (PLSc) they would have arrived at vastly different conclusions.[5] Moreover, it also implies these differences are solely attributable to the use of PLS. The onus rests on Evermann and Rönkkö (2023) to provide meaningful evidence for this extraordinary claim.

Giving Evermann and Rönkkö (2023) the benefit of doubt, we decided to assess how PLS, PLSc, and CBSEM perform in practical situations in the presence of zero and weak relationships in a nomological network, as claimed by Evermann and Rönkkö (2023). Our simulation draws on the UTAUT model with three different set-ups and assumes a common factor model population, as Evermann and Rönkkö (2023) do, and not a composite model population where PLS has well-known advantages over CBSEM and PLSc (Sarstedt et al., 2016). Case 1 has no relations between any of the constructs. Case 2 has very weak relationships of 0.05 in the population, while Case 3 has weak relationships of 0.1 (Figure 1). We also added an incorrect path from FC to BI to assess if the misspecification is detected. We ran 5,000 replications for all population models with a sample size of 500 and 2,000 bootstrap resamples. We used the *cSEM* (Rademaker & Schuberth, 2021) and *lavaan* packages (Rosseel et al., 2021) for this simulation.

[4] Note that this analysis is very conservative as we only considered the main models documented in each paper.

[5] As PLSc was introduced by Dijkstra (2014; see also Dijkstra & Henseler, 2015), its possible role in the development of seminal theories, even in a counterfactual world, is at best hypothetical.



Notes: Dashed arrow signifies the misspecified path; PE = Performance expectancy, EE = Effort expectancy, SI = Social influence; FC = Facilitating conditions; BI = Behavioral intention; USE = Use behavior.

Figure 1. Simulation Models

Table 1 shows that PLS and CBSEM almost always provided admissible solutions, while PLSc rarely produced admissible solutions in these specific conditions. This calls into question Evermann and Rönkkö's (2023) recommendation #1.[6] Thus, we restrict further discussion to PLS and CBSEM.

Table 1. Percentage of Admissible Solutions

	PLS			PLSc			CBSEM		
Case	**1**	**2**	**3**	**1**	**2**	**3**	**1**	**2**	**3**
Percentage of admissible solutions	99.4%	99.8%	100%	0.6%	1.1%	4.6%	100%	100%	100%

Note: In PLS and PLSc a solution is categorized as admissible if all the following hold: (1) Convergence achieved, (2) All absolute standardized loading estimates ≤ 1, (3) construct variance-covariance matrix is positive semi-definite, (4) all reliability estimates ≤ 1, and (5) model-implied indicator variance-covariance matrix is positive semi-definite. In CBSEM, a solution is categorized as inadmissible if either the algorithm did not converge or if a Heywood case is detected.

Table 2 presents simulation results. We consider Type-I error rates for all zero-effects and power for non-zero effects. For Case 1 (zero-effect case), PLS correctly finds no relation between the constructs indicating that the method is unbiased in this case. The variance of the PLS estimates is slightly higher than CBSEM by about 0.002. However, the PLS percentile bootstrap accounts for the fluctuation, producing a Type-1 error rate only marginally higher than 0.05, whereas the PLS bias-corrected and accelerated (BCa) bootstrap is more conservative. Overall, both PLS and CBSEM perform to the standards expected for Type-I error rate.

In Cases 2 and 3, both PLS and CBSEM estimates are very close to the population value with differences in the third decimal place averaged across all runs. In contrast to Case 1, the variance of the PLS estimates is less than CBSEM for Case 3, showing that PLS estimates are more stable than CBSEM across runs in this setting. The power of the PLS percentile bootstrap is slightly higher than CBSEM for both Cases 2 and 3, whereas it is lower for PLS BCa bootstrap. The Type-I error rate for the misspecified path between FC and BI demonstrates that both PLS and CBSEM can reliably detect it at the 5% level in all cases.[7]

[6] We also specified a more complex simulation model based on the European customer satisfaction index model (Tenenhaus et al., 2005) with zero relations between the constructs with sample size 500. Here the fraction of admissible solutions produced by CBSEM dropped sharply to approximately 28% (and 0.6% for PLSc), while PLS maintained 99.3% admissible solution rate, suggesting that both CBSEM and PLSc struggle to provide admissible solutions in more complex nomological networks with zero-effects.

[7] We also ran these simulations using sample size 50. CBSEM had a small drop in the percentage of admissible solutions (~92%), while PLS maintained its rate (~99%). While we find slightly elevated Type-I error rates and variance, and lower power for both PLS and CBSEM, the pattern of differences among the techniques are the same as the case with a sample size of 500.

Table 2. Simulation Results

Path	Method	Average / variance			Fraction of null hypothesis rejections		
		Case 1	Case 2	Case 3	Case 1 (Type-I error)	Case 2 (Power)	Case 3 (Power)
PE → BI	PLS	0.001 / 0.005	0.053 / 0.004	0.095 / 0.002	0.067 / 0.033	0.187 / 0.095	0.509 /0.326
	CBSEM	0.001 / 0.003	0.051 / 0.003	0.099 / 0.003	0.058	0.172	0.488
EE → BI	PLS	0.000 / 0.005	0.052 / 0.004	0.097 / 0.002	0.06 / 0.033	0.173 / 0.085	0.515 / 0.336
	CBSEM	0.000 / 0.003	0.049 / 0.003	0.100 / 0.003	0.051	0.158	0.493
SI → BI	PLS	-0.002 / 0.004	0.052 / 0.003	0.093 / 0.002	0.062 / 0.025	0.177 / 0.088	0.499 / 0.329
	CBSEM	-0.002 / 0.003	0.051 / 0.003	0.100 / 0.003	0.051	0.159	0.474
FC → USE	PLS	0.000 / 0.005	0.054 / 0.003	0.095 / 0.002	0.061 / 0.031	0.177 / 0.072	0.500 / 0.280
	CBSEM	0.000 / 0.003	0.051 / 0.003	0.100 / 0.003	0.052	0.163	0.487
BI → USE	PLS	0.000 / 0.003	0.047 / 0.003	0.091 / 0.002	0.059 / 0.031	0.160 / 0.094	0.492 / 0.376
	CBSEM	0.000 / 0.003	0.049 / 0.003	0.100 / 0.003	0.055	0.155	0.487
Misspecified path	**Method**	**Average / variance**			**Fraction of null hypothesis rejections**		
		Case 1	**Case 2**	**Case 3**	**Case 1 (Type-I error)**	**Case 2 (Type-I error)**	**Case 3 (Type-I error)**
FC → BI	PLS	0.000 / 0.003	0.000 / 0.003	0.001 / 0.002	0.052 / 0.034	0.053 / 0.030	0.049 / 0.034
	CBSEM	0.000 / 0.003	0.000 / 0.003	0.001 / 0.002	0.051	0.049	0.048

Note: The “Average / variance” columns refer to the average and variance of the path estimates across all runs. The “Fraction of null hypothesis rejections” columns for PLS are based on p-values from percentile / BCa bootstrap confidence intervals, and CBSEM p-values. They represent the fraction of times (across all runs) the null hypothesis is rejected at the 5% significance level.

These results clearly show that PLS reliably estimates common factor models with zero and weak relationships with marginal differences from CBSEM. That is, even if seminal IS models had included zero paths, the use of PLS could not have created major theoretical discrepancies, especially given the numerous replication studies that were conducted later with CBSEM and updated PLS inference methods. Replication and meta-analyses are important error-correction mechanisms in this regard. Furthermore, estimating the same model with PLS and CBSEM on practical datasets typically shows marginal differences, producing similar implications[8]. In fact, Blut et al.’s (2022) meta-analysis shows that theoretical discrepancies in UTAUT studies are largely explained by considering contextual effects (e.g., age, cultures, technologies). Thus, Evermann and Rönkkö's (2023) extraordinary claim that the use of PLS, per se, has caused “significant” damage to IS research is extremely dubious. Note that the simulation discussion above pertains to PLS being used exclusively in the in-sample explanation mode (Type-I error and Power). Considering that PLS additionally allows out-of-sample prediction assessments enhances its appeal further (Liengaard et al., 2021).

3 Discussion

PLS has been used to create many seminal IS models. While we may debate about the value of these theoretical achievements (e.g., Blut et al., 2022), the fact remains these models have stood the test of time and represent hard-earned achievements of IS researchers. They also point to the robustness of the original PLS analyses and results.

Science is not error-free, but rather error-correcting (Sarstedt et al., 2022). Oddly, it was PLS’s strength in providing a solution in most conditions that led to its misapplication in some studies and the ensuing criticisms. In contrast, CBSEM’s weakness in converging with complex models has shielded it from such criticisms. No technique can guard against a weak research design. The IS community has been quick to issue error-correcting calls for the appropriate use of PLS, rather than serving as critiques of the method itself (e.g., Marcoulides & Chin, 2013; Marcoulides & Saunders, 2006; Ringle et al., 2012).

Methodological improvements in PLS have come thick and fast. Old model evaluation practices have been substantially revised and strengthened within the last decade making it difficult for editors, reviewers, and researchers to be fully abreast. Recent work has sought to address this situation via updated guidelines and proper use of PLS in IS research (Hair, 2021; Petter & Hadavi, 2021). Thus, in so far as the overarching goal is to objectively evaluate the strengths and weaknesses of PLS applications, the issues regarding the use of outdated practices (small samples, *t*-values) raised by Evermann and Rönkkö

[8] We conducted this analysis for both TAM and UTAUT models and empirical data and report the results on https://www.pls-sem.net/various/

(2023) should be welcomed—although these have already been addressed several times (e.g., Goodhue et al., 2012; Marcoulides et al., 2012). As with any multivariate analysis method, the use of outdated practices should be dealt with at the editorial level, if such papers do arrive for review.

Scientific progress requires continuous epistemic and methodological iterations to refine both theories and methods (Elliott, 2012). There is uncertainty in the process—and it takes time. As researchers use and develop PLS, more knowledge regarding its strengths and weaknesses will emerge. The tenets of science require us to exercise humility and accept ambiguities inherent in the scientific process and to suspend judgement until all the evidence is in. They also require full consideration of available evidence, rather than cherry-picking results catering to a preferred storyline.

Evidence regarding PLS's abilities is now pouring in. Recent developments have brought PLS to the forefront of model evaluation using both explanatory and predictive lenses simultaneously, which was previously completely absent (Sharma et al., forthcoming; Shmueli et al., 2016, 2019). This contrasts with CBSEM which is an explanation-focused method. When the goal is to balance explanation with prediction, as is often the case, PLS is a valuable technique (Shmueli et al., 2019). Being armed with multiple methods (focusing on explanation, prediction, and explanation-prediction) enables scholars to channel their combined theoretical efforts over time toward a more stable scientific-tripod and develop a full spectrum of IS theories described by Gregor (2006). PLS plays an important role in this paradigm.

References

Apel, H., & Wold, H. (1982). Soft modeling with latent variables in two or more dimensions: PLS estimation and testing for predictive relevance. In K. G. Jöreskog & H. Wold (Eds.), *Systems under indirect observations: Part II* (pp. 209-247). North-Holland.

Athey, S. (2017). Beyond prediction: Using big data for policy problems. *Science, 355*(6324), 483-485.

Becker, J.-M., Rai, A., & Rigdon, E. E. (2013). Predictive validity and formative measurement in structural equation modeling: Embracing practical relevance. In *Proceedings of the International Conference on Information Systems.*

Blut, M., Chong, A. Y. L., Tsiga, Z., & Venkatesh, V. (2022). Meta-analysis of the unified theory of acceptance and use of technology (UTAUT): Challenging its validity and charting a research agenda in the red ocean. *Journal of the Association for Information Systems, 23*(1), 13-95.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2018). Double/debiased machine learning for treatment and structural parameters. *The Econometrics Journal, 21*(1), C1-C68.

Dijkstra, T. K. (2014). PLS' Janus face—response to Professor Rigdon's “rethinking partial least squares modeling: in praise of simple methods”. *Long Range Planning, 47*(3), 146-153.

Dijkstra, T. K., & Henseler, J. (2015). Consistent partial least squares path modeling. *MIS Quarterly, 39*(2), 297-316.

Elliott, K. C. (2012). Epistemic and methodological iteration in scientific research. *Studies in History and Philosophy of Science Part A, 43*(2), 376-382.

Evermann, J., & Rönkkö, M. (2023). Recent developments in PLS. *Communications of Association for Information Systems,52.*

Evermann, J., & Tate, M. (2016). Assessing the predictive performance of structural equation model estimators. *Journal of Business Research, 69*(10), 4565-4582.

Friedman, J. H. (1997). On bias, variance, 0/1—loss, and the curse-of-dimensionality. *Data Mining and Knowledge Discovery, 1*(1), 55-77.

Geman, S., Bienenstock, E., & Doursat, R. (1992). Neural networks and the bias/variance dilemma. *Neural Computation, 4*(1), 1-58.

Goodhue, D. L., Lewis, W., & Thompson, R. (2012). Does PLS have advantages for small sample size or non-normal data? *MIS Quarterly, 36* (3), 981-1001.

Goodhue, D. L., Lewis, W., & Thompson, R. (2015). PLS pluses and minuses in path estimation accuracy. In *Proceedings of the Twenty-first Americas Conference on Information Systems.*

Greene, B., (2015). Why string theory still offers hope we can unify physics. *Smithsonian Magazine*. Retrieved from www.smithsonianmag.com/science-nature/string-theory-about-unravel-180953637/

Gregor, S. (2006). The nature of theory in information systems. *MIS Quarterly, 30*(3), 611-642.

Hair, J. F. (2021). Reflections on SEM: An introspective, idiosyncratic journey to composite-based structural equation modeling. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 52*(SI), 101-113.

Hair, J. F., & Sarstedt, M. (2021). Explanation plus prediction: The Logical focus of project management research. *Project Management Journal, 52*(4), 319-322.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: Data mining, inference, and prediction* (2nd ed.). Springer.

Henseler, J., Dijkstra, T. K., Sarstedt, M., Ringle, C. M., Diamantopoulos, A., Straub, D. W., Ketchen, D. J., Hair, J. F, Hult, G. T. M., & Calantone, R. J. (2014). Common beliefs and reality about partial least squares: Comments on Rönkkö & Evermann (2013). *Organizational Research Methods, 17*(2), 182-209.

Hofman, J. M., Sharma, A., & Watts, D. J. (2017). Prediction and explanation in social systems. *Science, 355*(6324), 486-488.

Hofman, J. M., Watts, D. J., Athey, S., Garip, F., Griffiths, T. L., Kleinberg, J., Margetts, H., Mullainathann, S., Salganik, M. J., Vazire, S., Vespignani, A., & Yarkoni, T. (2021). Integrating explanation and prediction in computational social science. *Nature, 595*(7866), 181-188.

Jöreskog, K. G., & Wold, H. (1982). The ML and PLS techniques for modeling with latent variables: Historical and comparative aspects. In K. G. Jöreskog & H. Wold (Eds.), *Systems under indirect observation: Part I* (pp. 263-270). North-Holland.

Kleinberg, J., Ludwig, J., Mullainathan, S., & Obermeyer, Z. (2015). Prediction policy problems. *American Economic Review, 105*(5), 491-495.

Liengaard, B., Sharma, P. N., Hult, G. T. M., Jensen, M. B., Sarstedt, M., Hair, J. F., & Ringle, C. M. (2021). Prediction: Coveted, yet forsaken? Introducing a cross-validated predictive ability test in partial least squares path modeling. *Decision Sciences, 52*(2), 362-392.

Lohmöller, J.-B. (1989). *Latent variable path modeling with partial least squares*. Physica.

Marcoulides, G. A., & Chin, W. W. (2013). You write, but others read: Common methodological misunderstandings in PLS and related methods. In H. Abdi, W. W. Chin, V. Esposito Vinzi, G. Russolillo, & L. Trinchera (Eds.), *New perspectives in partial least squares and related methods* (vol. 56, pp. 31-64). Springer.

Marcoulides, G. A., Chin, W. W., & Saunders, C. (2012). When imprecise statistical statements become problematic: A response to Goodhue, Lewis, and Thompson. *MIS Quarterly, 36*(3), 717-728.

Marcoulides, G. A., & Saunders, C. (2006). PLS: A silver bullet? *MIS Quarterly, 30*(2), III-IX.

Petter, S. (2018). “Haters gonna hate”: PLS and information systems research. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 49*(2), 10-13

Petter, S., & Hadavi, Y. (2021). With great power comes great responsibility: The use of partial least squares in information systems research. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems, 52*(SI), 10-23.

Rademaker, M. E., & Schuberth, F. (2021). R package cSEM: Composite-based structural equation modeling (version 0.4.0). Retrieved from https://cran.r-project.org/web/packages/cSEM/

Ranstam, J., & Cook, J. A. (2018). LASSO regression. *British Journal of Surgery, 105*(10), 1348-1348.

Reinartz, W., Haenlein, M., & Henseler, J. (2009). An empirical comparison of the efficacy of covariance-based and variance-based SEM. *International Journal of Research in Marketing, 26*(4), 332-344.

Rigdon, E. E. (2016). Choosing PLS path modeling as analytical method in european management research: A realist perspective. *European Management Journal, 34*(6), 598-605.

Ringle, C. M., Sarstedt, M., & Straub, D. W. (2012). A critical look at the use of PLS-SEM in MIS Quarterly. *MIS Quarterly, 36*(1), iii-xiv.

Rönkkö, M., & Evermann, J. (2013). A critical examination of common beliefs about partial least squares path modeling. *Organizational Research Methods, 16*(3), 425-448.

Rosseel, Y., Jorgensen, T. D., & Rockwood, N. (2021). R package lavaan: Latent variable analysis (version 0.6-9). Retrieved from https://cran.r-project.org/web/packages/lavaan/

Sagan, C. (1989). *A personal voyage*. New Ballantine Books.

Sarstedt, M., & Danks, N. P. (2022). Prediction in HRM research: A gap between rhetoric and reality. *Human Resource Management Journal*, *32*(2), 485-513.

Sarstedt, M., Hair, J. F., & Ringle, C. M. (Forthcoming). “PLS-SEM: Indeed a silver bullet” – A retrospective and recent advances. *Journal of Marketing Theory & Practice*.

Sarstedt, M., Hair, J. F., Ringle, C. M., Thiele, K. O., & Gudergan, S. P. (2016). Estimation issues with PLS and CBSEM: Where the bias lies! *Journal of Business Research, 69*(10), 3998-4010.

Sharma, P. N., Liengaard, B., Hair, J. F., Sarstedt, M., & Ringle, C. M. (Forthcoming). Predictive model assessment and selection in composite-based modeling using PLS-SEM: Extensions and guidelines for using CVPAT. *European Journal of Marketing.*

Sharma, P. N., Sarstedt, M., Shmueli, G., Kim, K. H., & Thiele, K. O. (2019). PLS-based model selection: The role of alternative explanations in information systems research. *Journal of the Association for Information Systems, 20*(4), 346-397.

Shmueli, G. (2010). To explain or to predict? *Statistical Science, 25*(3), 289-310.

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly, 35*(3), 553-572.

Shmueli, G., Ray, S., Velasquez Estrada, J. M., & Chatla, S. B. (2016). The elephant in the room: Evaluating the predictive performance of PLS models. *Journal of Business Research, 69*(10), 4552-4564.

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: Guidelines for using PLSpredict. *European Journal of Marketing, 53*(11), 2322-2347.

Tenenhaus, M., Esposito Vinzi, V., Chatelin, Y.-M., & Lauro, C. (2005). PLS path modeling. *Computational Statistics & Data Analysis, 48*(1), 159-205.

Wager, S., & Athey, S. (2018). Estimation and inference of heterogeneous treatment effects using random forests. *Journal of the American Statistical Association, 113*(523), 1228-1242.

Wold, H. (1982). Soft modeling: The basic design and some extensions. In K. G. Jöreskog & H. Wold (Eds.), *Systems under indirect observations: Part II* (pp. 1-54). North-Holland.

Wold, H. (2006). Partial least squares. In S. Kotz, C. B. Read, N. Balakrishnan, B. Vidakovic, & N. L. Johnson (Eds.), *Encyclopedia of statistical sciences*. Wiley.

Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science, 12*(6), 1100-1122.

About the Authors

Pratyush N. Sharma is an assistant professor in the department of Information Systems, Statistics, and Management Science in the University of Alabama's Culverhouse College of Business. His research interests include online collaboration communities, open-source software development, technology use and adoption, and research methods used in information systems, particularly partial least squares path modeling. His research has been published in highly acclaimed journals such as the Journal of the Association for Information Systems, Journal of Retailing, Decision Sciences, Journal of Information Systems, Journal of Business Research, and Journal of International Marketing.

Benjamin D. Liengaard is an assistant professor in the Department of Economics and Business Economics, Aarhus University. His main research interest is in partial least squares path modeling and quantitative analysis in the field of business analytics. His research has been published in Decision Sciences.

Marko Sarstedt is a chaired professor of marketing at the Ludwig Maximilians University Munich, Germany, and an adjunct research professor at Babeș-Bolyai University, Romania. His main research interest is the advancement of research methods to further the understanding of consumer behavior. His research has been published in Nature Human Behaviour, Journal of Marketing Research, Journal of the Academy of Marketing Science, Multivariate Behavioral Research, Organizational Research Methods, MIS Quarterly, Decision Sciences, and Psychometrika, among others. Marko has been named member at Clarivate Analytics' Highly Cited Researchers List, which includes the "world's most impactful scientific researchers."

Joseph F. Hair, Jr. is Director of the PhD Program and Cleverdon Chair of Business, Mitchell College of Business, University of South Alabama. In 2018, 2019, 2020, and 2021, Joe was recognized by Clarivate Analytics for being in the top 0.1% globally of all Business and Economics researchers based on his citations and scholarly accomplishments. He has authored over 75 book editions and has published numerous articles in scholarly journals such as the Journal of Marketing Research, Journal of Academy of Marketing Science, European Journal of Marketing, Organizational Research Methods, Journal of Family Business Studies, Journal of Retailing, and others.

Christian M. Ringle is a chaired professor of management at the Hamburg University of Technology, Germany. His research addresses the field of management and quantitative methods for business analytics, machine learning, and market research. His articles have been published in journals such as Information Systems Research, International Journal of Human Resource Management, International Journal of Research in Marketing, Journal of the Academy of Marketing Science, Organizational Research Methods, and MIS Quarterly. Since 2018, he has been included in the Clarivate Analytics' Highly Cited Researchers list. More information about Dr. Ringle can be found at https://www.tuhh.de/hrmo/team/prof-dr-c-m-ringle.html

Copyright © 2023 by the Association for Information Systems. Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and full citation on the first page. Copyright for components of this work owned by others than the Association for Information Systems must be honored. Abstracting with credit is permitted. To copy otherwise, to republish, to post on servers, or to redistribute to lists requires prior specific permission and/or fee. Request permission to publish from: AIS Administrative Office, P.O. Box 2712 Atlanta, GA, 30301-2712 Attn: Reprints are via e-mail from publications@aisnet.org.